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ABSTRACT

The optimum weighting of variables to predict a dependent-criterion variable is an important problem in nearly all of the social and natural sciences. Although the predominant method, multiple regression analysis (MR), yields optimum weights for the sample at hand, these weights are not generally optimum in the population from which the sample was drawn. A method was developed that sacrifices some "prediction" in the sample at hand in order to achieve a more reliable and stable predictor composite. The method developed, Factor Regression Analysis (FRA) is based on the first principle component of the predictor intercorrelation matrix with validities in the diagonal cells. FRA yielded very stable predictor composites and weights--the weights themselves varied less from sample to sample than did MR weights from the same samples. These differences were marked for low sample sizes (e.g., N = 25), regardless of the number of variables in regression. With regard to prediction, FRA composites were substantially more valid in the population than the MR composites based on the same samples. The number of predictors in the subset did not turn out to be very important. FRA weights based on samples of 25 were about as valid as MR weights based on samples of 100. With samples of 200 the two methods yielded roughly equivalent prediction. (Author)

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FACTOR REGRESSION ANALYSIS: A NEW METHOD FOR WEIGHTING PREDICTORS

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FACTOR REGRESSION ANALYSIS: A NEW METHOD FOR WEIGHTING PREDICTORS

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

The optimum weighting of variables to predict a dependent/criterion variable is an important problem in nearly all of the social and natural sciences. Although the predominant method, multiple regression analysis (MR), yields optimum weights for the sample at hand, these weights are not generally optimum in the population from which the sample was drawn. A method was developed that sacrifices some "prediction" in the sample at hand in order to achieve a more reliable and stable predictor composite. The method developed, Factor Regression Analysis (FRA), is based on the first principle component of the predictor

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SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered) intercorrelation matrix with validities in the diagonal cells. FRA yielded very stable predictor composites and weights--the weights themselves varied less from sample to sample than did MR weights from the same samples. These differences were marked for low sample sizes (e.g., N = 25), regardless of the number of variables in regression. With regard to prediction, FRA composites were substantially more valid in the population than the MR composites based on the same samples. The number of predictors in the subset did not turn out to be very important. FRA weights based on samples of 25 were about as valid as MR weights based on samples of 100. With samples of 200 the two methods yielded roughly equivalent prediction.

FOREWORD

The early developmental work of this new method was conducted in support of the Interlaboratory Independent Research Program. During FY 1976 and 7TQ, it was supported by the Office of Naval Research.

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J. J. CLARKIN
Commanding Officer

SUMMARY

Problem

The optimum weighting of variables to predict a dependent criterion variable is an important problem in nearly all of the social and natural sciences. Although the predominant method, multiple regression analysis, yields optimum weights for the sample at hand, these weights are not generally optimum in the population from which the sample was drawn. However, all other multivariate methods proposed to date have provided poorer prediction in some samples and populations.

Objective

The objective was to develop and validate a multivariate method that would provide better prediction weights than existing methods. The weights would be more stable from sample to sample, and would predict the dependent/criterion variable more accurately in the population.

Approach

A method was developed that sacrifices some "prediction" in the sample at hand in order to achieve a more reliable and stable predictor composite. Multiple regression (MR) does the opposite, assuming completely reliable and trustworthy data. The method developed, Factor Regression Analysis (FRA), is based on the first principle component of the predictor intercorrelation matrix with validities in the diagonal cells.

Two kinds of data were used to evaluate FRA: Navy data and Monte Carlo data. Hundreds of samples were analyzed, and the weights were applied to the populations from which the samples were drawn. All predictor subset sizes were analyzed for each sample.

Findings

The new method, FRA, yielded very stable predictor composites and weights--the weights themselves varied less from sample to sample than did MR weights from the same samples. These differences were marked for low sample sizes (e.g., N = 25), regardless of the number of variables in regression. For large sample sizes (e.g., N = 200), the differences were smaller but still fairly consistent.

For small samples, FRA composites were much more valid in the population than the MR composites based on the same samples. The number of predictors in the subset did not turn out to be very important. FRA weights based on samples of 25 were about as valid as MR weights based on samples of 100. With samples of 200 the two methods yielded roughly equivalent prediction.

Conclusions

The new method, FRA, is a very important improvement upon multiple regression for small samples. In addition, FRA does not fail at the higher samples sizes as previously proposed methods have done. Thus, it can be used with confidence for all samples sizes as they occur in applied settings.

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INTRODUCTION

Problem

Since 1900, it has been commonly assumed that multiple-regression weights based on a sample are the best candidates for prediction weights in the population (see Gullikson, 1950, & Walker, 1958). Evidence that this is generally not true for small samples has been accumulating for many years (e.g., Horst, 1941; Guilford, 1954; Schmidt, 1971). Although several multivariate methods have been advocated in recognition of this fact (e.g., Horst, 1941; Kendall, Note 1; Rock, Linn, Evans, & Patrick, 1970), none have consistently excelled multiple regression, even with rather small samples (e.g., $N = 50$). In fact, a recent study (Rock et al., 1970) found that sample multiple-regression weights predicted Y in the population better than did weights computed by the other promising multivariate methods.

Multiple regression yields a predictor composite that is, for the sample at hand, maximally related to the criterion. However, in the process, multiple regression violates a principle for constructing a reliable composite: the higher the intercorrelation among the components of the composite, the higher the reliability of the composite (Moiser, 1943). When multiple regression computes the optimum weights, it computes the weight for each predictor while all other predictors are held constant. Thus, each predictor's weight is based on its validity after all the criterion-related variance that the predictor shares with the other predictors has been removed. In effect, each weight is based on a residual matrix or, equivalently, partial correlation. When two predictors are highly correlated, the one with the larger validity will tend to receive a representative weight and the other a much lower, or even negative weight. There is no overlap between any of the weights as far as accounting for criterion variance is concerned. Multiple-regression rules out any capitalization upon the redundancy that invariably exists among the predictors. In contrast, reliable composites tend to give great weight to intercorrelation among the predictors.

This inconsistency between reliability of the predictor composite, and optimum "prediction" in the sample at hand, can be seen in the formula for the standard error of multiple-regression weights. Examination of that formula leads to the unmistakable conclusion that the higher the correlations among the predictors, the higher the standard errors of the weights. This indicates an unreliable composite in a situation that should yield a very reliable composite. Beaton, Rubin, and Barone (1970) demonstrated this empirically, showing that the higher the intercorrelation, the more unstable the multiple-regression weights.

Another inadequacy in multiple regression has been referred to as the "partialling fallacy" (Gordon, 1968). As mentioned above, multiple regression is based on partial-correlational techniques. It determines optimum weights by partialling--each predictor's optimum weight is determined by partialling out association with the other predictors. Unfortunately, partial correlations are based on the assumptions that the variable being partialled out contains no unique component and is measured without error (Burks, 1926; Monroe & Stuit, 1935; Stephenson, 1935; Gordon, 1968). Few, if any, psychological tests and measurements satisfy both of these assumptions. Unfortunately, no publications could be found that demonstrated empirically how the fallacious partial correlations affected, or did not affect, multiple-regression weights or their validity.

It would appear, therefore, from several standpoints, that multiple regression does not give due consideration to the unreliability and complexity of the measures used throughout most of the behavioral and social sciences. Perhaps compromise between composite reliability and maximization of composite validity in the sample at hand, would yield better weights for prediction in the population.

Purpose

The purpose of this effort was to develop and validate a multivariate method that would provide better predictor weights than existing methods. These weights would be more stable from sample to sample and would predict the dependent/criterion variable more accurately in the population.

PROCEDURE

Factor Regression Analysis (FRA)

The method developed is called Factor Regression Analysis (FRA). Only the empirical steps in the actual procedure will be presented here. A presentation of FRA and its relationship to multiple regression, principle components, and factor analysis will be found in the discussion section.

Starting with the intercorrelation matrix of predictors, the unities in the main diagonal cells were replaced by validities--each predictor's validity was placed in the predictor's diagonal cell. The first principle component of this matrix was computed (Gulliksen, 1950, p. 346), and the loadings of the predictors on the first principle component were used as predictor weights.

Predictors were dropped in a step-wise manner by omitting the predictor with the smallest loading. The dropped predictor was omitted from the correlation matrix, and a new principle component was computed. This procedure was followed until only two predictors remained.

Multiple Regression

Step-wise multiple regression was used, since it was considered preferable to the "forward" selection and the "backward" elimination procedures (Kerlinger & Pedhazur, 1973). At each step, all possible combinations, of a particular size, were compared. The selected subset was the one that correlated highest with Y.

Test Data

Two kinds of data were used to compare FRA and multiple regression (MR): Navy data and Monte Carlo data. The Navy data consisted of 16,826 records for enlisted men, obtained from the Naval Examination Center. A composite variable, Final Multiple Score (FMS), which is used for the advancement (promotion) decision, was the criterion variable (Robertson, James, & Royle, 1972). Ten predictors were used: eight aptitude tests (the Navy Basic Test Battery), age, and amount of education (in years). The 16,826 records were placed in random order, and successive groups were used as samples. All of the records were used as the population.

Monte Carlo data were generated from published correlation matrices (Rock et al., 1970; McCornack, 1970). Predictors ranged in number from 11 to 15. A computer program (Moonan & Cohver, 1973, Note 2) was used to generate Monte Carlo samples based on the published correlation matrices.

Population Validity

The weights for each predictor set or subset were applied to the population through the use of the following formula:

$$r = \frac{\Sigma W_i r_{iY} \lambda_i}{\sqrt{\Sigma W_i^2 \lambda_i^2 + 2\Sigma r_{ij} W_i W_j \lambda_i \lambda_j}}$$

where:

W_i = sample weight for the i-th predictor,

r_{iY} = population validity of the i-th predictor,

$\lambda_i = \sigma_p/\sigma_s$--the standard deviation in the population, over the standard deviation in the sample, and

r_{ij} = population correlation between the i-th and j-th predictor.

This is called the "population validity." It indicates how well the sample weights would work in the population. FRA and MR weights were evaluated using this formula.

Computer Program

A computer program was developed for the GA1830 Computer to perform the calculations.

RESULTS

The intercorrelation matrix for the "population" of Navy data (N = 16,826) is presented in Table 1. Multiple-regression weights for these data were:

X Variable:	1	2	3	4	5	6	7	8	9	10
MR Weight :	.15	.08	.12	-.01	.01	-.05	.11	.11	.07	.09

The multiple correlation was .46. In the first sample (N = 25), the weights were:

MR Weight :	.10	-.55	.49	.21	-.49	.04	.62	-.04	.28	-.25
FRA Weight:	.30	.28	.54	.26	.10	.18	.55	.34	.08	.09

These weights yielded a population validity of .24 in the case of MR, and .42 in the case of FRA. Sample validities for these two sets of weights were .75 and .56, respectively.

Table 1

Intercorrelation Matrix for the Navy Data
(N = 16,826)

	Y	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
Y	--	33	28	26	04	09	05	34	28	20	25
X_1		--	56	14	16	21	30	61	21	17	38
X_2			--	07	21	09	24	58	12	19	33
X_3				--	-04	18	02	22	68	03	00
X_4					--	08	28	15	-07	04	20
X_5						--	34	18	14	-03	07
X_6							--	24	-01	02	15
X_7								--	27	19	35
X_8									--	04	05
X_9										--	57
X_{10}											--

Note: Decimal points have been omitted from correlations.

Table 2 presents the average population validity in 10 samples. This is given separately for four sample sizes (25, 50, 100, and 200), as well as for predictor subsets of all possible sizes. Of most interest in the table is the "Mean Difference" column. It shows the difference, on the average, in the population validities for MR and FRA weights given in the first two columns. Each value refers to a different predictor subset size from 2 to 10. It can be seen that the FRA weights were much more valid than the MR weights. Except for very small subsets, e.g., two or three, it mattered little how many predictors were in the subset.

The mean differences were quite large in many instances, e.g., 15 or so correlation points. Even with only four predictors in the subset and an N of 50, the mean difference was 11. In general, FRA weights based on samples of 25 were as valid as MR weights based on samples of 100.

For the largest samples (N = 200), MR weights were a little better for the small subsets of two or three predictors. However, FRA weights achieved an average validity of .43 with six predictors, a level never achieved by MR weights for any subset.

Standard deviations of the population validities across 10 samples are presented in the last two columns of Table 2. As can be seen, the population validities differed greatly for MR but not for FRA. In fact, they were nearly as consistent, in the case of FRA, when N = 25 as when N = 200. This was definitely not true for MR.

The standard deviations of the predictor weights, as opposed to the standard deviations of the population validities, are presented in Table 3. These standard deviations pertain only to the weights when all predictors were in regression. The variability of each predictor's weight across 10 samples is indicated for MR and FRA. It can be seen that the FRA weights were much more stable on the average. This is especially true for small samples. However, even when N = 200, the MR weight for predictors four, six, and ten varied much more than the FRA weight.

Before proceeding to other populations, the selection of predictors for inclusion in the subsets should be examined. Table 4 shows the percentage of predictors in common for the MR and FRA subsets when N = 50. It is clear that MR and FRA did not use the same predictors. Results for the other sample sizes were almost identical and are, therefore, not given here. Sample size was simply not important in this respect. In no case, even for large samples, was there complete overlap in the small subsets. Further, there were many cases in which only one-third are common. The last column shows the average percent for each subset size.

Three other "populations" were used to evaluate FRA, as was done above using Navy data. There is one important difference, however. Instead of using whatever data were available, published data that had been analyzed in journal articles were used. This enabled the comparison of results, and the choice of widely differing populations.

Table 2

Population Validities of MR and FRA Composites for Navy Data

Number of Predictors in Regression	Average Population Validity MR	Average Population Validity FRA	Mean Difference	Standard Deviation MR	Standard Deviation FRA
		N = 25			
2	27	32	05	13	07
3	26	37	11	13	04
4	27	38	11	13	03
5	25	40	15	11	03
6	26	40	14	11	03
7	25	41	16	11	03
8	25	41	16	10	03
9	25	42	17	10	02
10	25	42	17	10	03
		N = 50			
2	32	34	02	11	04
3	30	37	07	10	03
4	28	39	11	11	04
5	28	38	10	11	04
6	28	38	10	11	05
7	27	40	13	12	05
8	27	40	13	11	04
9	27	41	14	12	03
10	27	41	14	12	03
		N = 100			
2	35	33	-02	04	05
3	38	36	-02	06	02
4	38	39	01	05	02
5	38	40	02	04	03
6	37	41	04	05	04
7	36	41	05	06	04
8	36	41	05	05	03
9	36	42	06	05	03
10	36	42	06	05	02
		N = 200			
2	38	34	-04	01	04
3	40	36	-04	02	02
4	41	40	-01	02	01
5	42	42	00	02	03
6	42	43	01	02	03
7	41	43	01	02	03
8	41	42	01	02	03
9	41	42	01	02	02
10	41	42	01	02	01

Note: Decimal points have been omitted.

Table 3

Standard Deviation of Weights Across 10 Samples of Navy Data

Weights	Predictor 1	2	3	4	5	6	7	8	9	10
					N = 25					
MR	.29	.35	.30	.20	.31	.23	.21	.21	.25	.29
FRA	.19	.12	.20	.15	.05	.06	.08	.12	.08	.21
					N = 50					
MR	.14	.12	.14	.07	.06	.09	.12	.15	.15	.13
FRA	.06	.12	.13	.10	.10	.09	.08	.15	.16	.11
					N = 100					
MR	.11	.19	.12	.13	.05	.06	.18	.10	.16	.10
FRA	.04	.06	.04	.05	.08	.08	.06	.07	.15	.06
					N = 200					
MR	.06	.09	.10	.10	.03	.10	.07	.08	.08	.11
FRA	.02	.05	.11	.02	.03	.04	.04	.07	.06	.04

Table 4

Percentage of Predictors in Common for the MR and FRA Subsets

Number of Predictors in Regression	Sample 1	2	3	4	5	6	7	8	9	10	Average Percentage
2	50	50	50	50	50	50	00	50	50	50	45
3	67	33	33	33	33	67	00	33	67	33	38
4	75	50	75	75	50	50	25	25	50	25	50
5	60	40	80	60	40	40	40	20	60	60	50
6	67	67	83	67	50	50	67	33	50	67	60
7	71	71	86	71	71	71	86	57	71	71	73
8	75	87	87	87	75	87	87	75	75	87	82
9	89	89	89	89	89	89	100	89	89	89	90
10	100	100	100	100	100	100	100	100	100	100	100

Two of the populations used were analyzed in a journal article (Rock et al., 1970) that compared several predictor weighting and selection techniques--including multiple regression. In that study, multiple-regression weights were shown to be better than weights derived by any of the other techniques. If FRA weights are more valid on these data, it would be very strong evidence, indeed, for the method's utility. Furthermore, the two populations were originally chosen by Rock et al. (1970) because they differed greatly in terms of level of validities and level of predictor intercorrelation.

The intercorrelation matrices of the two Rock et al., (1970) populations are presented in Tables 5 and 6, and average population validities for 10 Monte Carlo samples are presented in Tables 7 and 8. By and large, the results substantiate the results for Navy data. The FRA weights were much more valid for $\underline{N} = 25$ and nearly identical to MR weight validities for $\underline{N} = 200$. As in the case of Navy data, FRA weights based on samples of 25 were about as valid as MR weights based on samples of 100. Even when the subset contained only two predictors, FRA weights were as valid as MR weights.

Sample-to-sample fluctuations of the population validities for FRA were very small, as indicated by the standard deviations given in the last column of the tables. For example, in Table 7, when $\underline{N} = 25$ and when 12 predictors were in regression, the standard deviation of population validities were .01 for FRA, compared to .15 for MR. This is for an average validity of .71 for FRA and .52 for MR. Comparing this with $\underline{N} = 100$ and 12 predictors, the average population validity for MR is now .71 also, but its standard deviation is .02--still not as low as the standard deviation for FRA when $\underline{N} = 25$.

Table 5

Intercorrelation Matrix for Rock I

	Y	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
Y	--	55	58	64	61	56	64	62	61	40	41	45	43
X_1		--	58	66	66	66	64	65	73	49	45	46	46
X_2			--	70	66	64	65	68	57	45	52	49	49
X_3				--	79	76	73	80	65	52	60	63	57
X_4					--	75	79	80	63	54	56	59	57
X_5						--	70	76	61	51	54	58	56
X_6							--	78	65	54	56	56	56
X_7								--	65	63	67	66	66
X_8									--	47	43	44	47
X_9										--	56	51	54
X_{10}											--	59	62
X_{11}												--	55
X_{12}													--

Note: Decimal points have been omitted from correlations.

Table 6

Intercorrelation Matrix for Rock II

	Y	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
Y	--	15	-05	36	19	24	26	20	09	12	31	22	16
X_1		--	26	30	23	15	19	11	06	05	18	13	10
X_2			--	-05	09	10	11	-03	-03	01	-02	05	03
X_3				--	56	47	40	34	13	10	51	33	22
X_4					--	50	42	24	15	12	42	24	27
X_5						--	35	19	01	15	28	16	20
X_6							--	21	13	09	28	28	23
X_7								--	13	06	29	15	14
X_8									--	06	22	38	07
X_9										--	10	01	12
X_{10}											--	36	22
X_{11}												--	26
X_{12}													--

Note: Decimal points have been omitted from correlations.

Table 7

Population Validities of MR and FRA Composites For Rock I

Number of Predictors in Regression	Average Population Validity MR	Average Population Validity FRA	Mean Difference	Standard Deviation MR	Standard Deviation FRA
		N = 25			
2	65	68	03	04	02
3	63	69	06	06	03
4	60	71	11	10	03
5	57	71	14	13	03
6	55	71	16	15	02
7	55	71	16	15	02
8	53	71	18	15	02
9	53	71	18	16	01
10	53	71	18	15	01
11	52	71	19	15	01
12	52	71	19	15	01
		N = 50			
2	70	70	00	01	01
3	68	70	02	04	01
4	67	71	04	04	01
5	67	71	06	03	01
6	66	72	06	04	01
7	66	72	07	04	01
8	65	72	08	04	01
9	64	72	08	04	01
10	64	72	08	04	01
11	63	71	08	05	01
12	63	71	08	05	00
		N = 100			
2	70	69	-01	01	01
3	71	70	-01	02	01
4	71	71	00	02	01
5	71	72	01	02	01
6	71	72	01	02	01
7	71	72	01	02	00
8	71	72	01	02	00
9	71	72	01	02	00
10	71	72	01	02	00
11	71	72	01	02	00
12	71	71	00	02	00
		N = 200			
2	70	70	00	01	01
3	72	71	-01	01	00
4	72	72	00	01	01
5	72	72	00	01	00
6	73	72	-01	00	01
7	73	72	-01	00	01
8	73	72	-01	01	00
9	72	72	00	01	00
10	72	72	00	01	00
11	73	72	-01	01	00
12	73	71	-02	01	00

Note: Decimal points have been omitted.

Table 8

Population Validities of MR and FRA Composites for Rock II

Number of Predictors in Regression	Average Population Validity MR	FRA	Mean Difference	Standard Deviation MR	FRA
		N = 25			
2	29	34	05	10	07
3	30	38	08	08	04
4	31	39	08	06	03
5	29	40	11	07	01
6	29	40	11	07	02
7	27	40	13	08	02
8	27	40	13	09	02
9	27	40	13	09	02
10	27	40	13	09	02
11	27	40	13	09	02
12	27	40	13	09	02
		N = 50			
2	34	36	02	08	07
3	34	39	05	08	05
4	35	39	04	07	02
5	35	40	05	08	01
6	34	40	06	09	01
7	35	41	06	09	01
8	34	41	07	08	01
9	35	41	06	08	01
10	34	41	07	08	01
11	34	41	07	09	01
12	34	41	07	09	01
		N = 100			
2	36	39	03	04	02
3	36	39	03	08	01
4	36	39	03	08	02
5	37	39	02	04	01
6	37	39	02	04	00
7	38	39	01	04	00
8	38	39	01	04	00
9	38	39	01	04	00
10	39	38	-01	04	01
11	39	38	-01	04	00
12	39	37	-02	04	00
		N = 200			
2	38	39	01	02	02
3	37	39	02	02	02
4	38	39	01	02	02
5	39	39	00	02	01
6	40	39	-01	02	01
7	40	39	-01	02	00
8	40	38	-02	02	00
9	40	39	-01	02	00
10	40	38	-02	02	01
11	39	37	-02	02	00
12	39	38	-01	02	00

Note: Decimal points have been omitted.

Similar results are presented in Table 8 for the other population from Rock et al., (1970). FRA performed even better than in previous populations for small (two or three) predictor subsets. The average population validity for FRA with two predictors was higher than it was for MR in every sample size. True, the differences are small for the larger sample sizes. When N = 100, however, there was much less fluctuation from sample-to-sample for FRA validities. When N = 200, the FRA validities were still more stable, in general, than the MR validities.

The fourth population--like the second and third populations--also had been analyzed in a previous journal article--one devoted to comparing population validities of predictor selection techniques (McCornack, 1970). Table 9 contains the intercorrelation matrix, and Table 10, the comparitive results. Since these tables include 15 predictors, the samples of 25 are dangerously close to total instability for multiple regression purposes. However, FRA performed very well, indeed. It gave a high and very stable population validity at all subset sizes. Its average population validity with 15 predictors in regression was .81--16 correlation points above the one for MR, and its standard deviation was only .02 across the 10 samples.

With sample sizes of 50, MR achieved high population validities, but they were less stable than the FRA validities. Except for small subsets, MR and FRA performed equally well in the larger samples. In the small subsets, e.g., when only two or three predictors were in regression, FRA excelled. Even when N = 200, FRA gave a higher and more stable population validity for the two-predictor subset.

Population validities for unit weights were also computed for all four populations. Various studies have shown that unit weights often yield higher cross-validation than MR weights when small samples are used (e.g., Perloff, 1951, Note 3; Schmidt, 1971). With all predictors in regression, and N = 25, the population validities for FRA were larger than the population validities for unit weights--.07, .03, .03, and .26 correlation points in the four populations, respectively.

Additional analyses were also conducted in order to test the feasibility and desirability of using the second principle component to enhance prediction. The mathematical procedure for combining the second component with the first component so as to optimally predict Y was formulated.[1] Basically, it involved the computation of the best least square weighting vector for estimating the sample Y from the first two principle components. This procedure did not enhance prediction of Y in any of the populations. In fact, in general there was a slight attenuation (.01) of the prediction provided by the first component alone.

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[1]The author is indebted to Paul Horst for his assistance.

Table 9

Intercorrelation Matrix from McCornack

	Y	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}
Y	--	45	72	79	33	-09	-09	02	07	-05	17	06	09	-23	-29	-25
X_1		--	52	35	17	-09	-01	02	-09	06	00	-21	04	08	11	04
X_2			--	66	27	-11	-01	03	-01	-04	13	-01	02	-05	-14	-13
X_3				--	30	-03	-06	02	02	-05	14	06	09	-20	-18	-17
X_4					--	-02	00	03	-11	04	03	-04	03	-01	06	00
X_5						--	-43	-22	33	-10	-18	03	03	-05	-03	14
X_6							--	00	-01	27	-17	-02	00	01	11	-04
X_7								--	-35	-16	-26	04	-02	-02	03	-16
X_8									--	-21	-35	07	01	-06	-23	-22
X_9										--	-16	-12	05	08	23	-10
X_{10}											--	10	-02	-11	-33	-16
X_{11}												--	-49	-42	-38	-12
X_{12}													--	-35	06	04
X_{13}														--	32	10
X_{14}															--	37
X_{15}																--

Note: Decimal points have been omitted from correlations.

Table 10
Population Validities of MR and FRA
Composites for McCornack Data

Number of Predictors in Regression	Average Population Validities MR	Average Population Validities FRA	Mean Difference	Standard Deviation MR	Standard Deviation FRA
		N = 25			
2	78	80	02	03	02
3	78	81	03	03	01
4	78	81	03	04	01
5	77	81	04	04	01
6	76	81	05	06	01
7	76	81	05	07	02
8	74	81	07	09	02
9	74	81	07	09	02
10	72	81	09	09	02
11	70	81	11	09	02
12	69	81	12	09	02
13	67	81	14	09	02
14	68	81	13	09	02
15	65	81	16	10	02
		N = 50			
2	80	83	03	03	00
3	81	83	02	03	00
4	82	84	02	03	01
5	82	84	02	04	01
6	82	84	02	04	01
7	82	84	02	04	01
8	81	84	03	05	01
9	81	84	03	06	01
10	81	84	03	06	01
11	81	84	03	06	01
12	81	84	03	06	01
13	81	84	03	05	01
14	81	84	03	05	01
15	81	84	03	06	01
		N = 100			
2	81	83	02	01	00
3	83	84	01	01	00
4	83	84	01	01	00
5	83	84	01	01	00
6	84	84	00	01	01
7	84	85	01	01	01
8	84	84	00	01	01
9	84	85	01	01	01
10	84	85	01	01	01
11	84	84	00	01	01
12	85	85	00	01	01
13	85	85	00	01	01
14	85	85	01	01	00
15	84	85	01	01	00
		N = 200			
2	80	83	03	01	00
3	83	84	01	01	00
4	84	84	00	01	00
5	83	84	01	01	00
6	83	84	01	01	00
7	84	84	00	01	00
8	84	84	00	01	01
9	84	84	00	01	01
10	84	84	00	01	01
11	84	84	00	01	01
12	84	84	00	01	01
13	84	85	01	01	01
14	84	85	01	01	01
15	84	85	01	01	02

Note: Decimal points have been omitted.

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DISCUSSION AND CONCLUSIONS

Factor Regression Analysis (FRA) went through a long developmental process. Thus, as presented above, it does not greatly resemble its earlier self. Nevertheless, judging from the reactions of colleagues to whom the author has presented FRA, its earlier forms and developments are very instructive and meaningful. Some years ago the author had become convinced that the mathematical process called multiple regression (MR) was far too precise for most of our samples--that it assumed far more stability and reliability than was present in our data. Therefore, it capitalized on chance to such an extent that weights based on sample were likely to be very poor in the population from which the sample was drawn. It was felt that some restraint could be placed on the mathematical process of weight determination by eliminating the actual Y scores while retaining the subjects' order on the Y scale. This was done by pairing subjects adjacent on the Y scale--the highest with the next highest, the third highest with the fourth highest, etc., until N/2 pairs were obtained.

The author suspected that these pairs could be used to compute "regression coefficients" for predicting Y, without directly using the Y scores. Obviously, the intrapair correlation on Y would be very high--it proved to be about .99, even with rather small samples (e.g., $\underline{N} = 50$). (This is an intraclass correlation--both axes of the response surface refer to the same variable, and a plotted point represents one subject-pair.)

What would the intrapair correlation be for a given <u>predictor</u> after matching on Y? The author felt this correlation would be, to some extent, dependent upon the predictor's validity, i.e., its correlation with Y. Conversations with other research psychologists and statisticians, however, revealed that the dependency, if it existed, was certainly not obvious. Consequently, the empirical path was chosen temporarily. A small subsample from a large sample of Navy data was used. All intrapair correlations were computed. The correlations were generally much smaller than the respective validities, but were rather obviously correlated with them. So, the possibility still remained that there was some dependency.

Simultaneously, a computer program was written that would compute an intrapair correlation for all the predictors combined, weighting them so as to maximize this correlation. (One can conceive of this as an "intraclass canonical" correlation--a battery of variables is optimally weighted to correlate with itself, each plotted point of the response surface representing a subject pair.) These weights were then applied to the large sample from which the subsample was drawn. It was discovered that they predicted Y quite well--better than the multiple-regression weights from the same subsample.

The computer program is based on Thomson's application (1940) of Hottelling's "most predictable criterion" solution (1935). Thomson showed how one could obtain the composite that is maximally reliable by computing the first principle component of a correlation matrix with reliabilities in the diagonal. In the present case, the correlation matrix for the predictors was used, with each predictor's diagonal cell containing its intrapair correlation. The first principle component of this correlation matrix yielded the weights that proved to predict Y in the population so well.

Meanwhile, a search of the literature revealed an article by McNemar (1940) which indicated that the expected value of the intrapair correlation for a given predictor might be its validity squared. A mathematical proof was developed and is presented in the appendix. Armed with this proof, it was no longer necessary to pair-off the subjects on the basis of their Y scores. The computer program was simply modified to use the squared validity instead of the intrapair correlation, in the respective diagonal cell. Subsequent experience revealed that the validity itself worked as well, or even better for some populations, than the validity squared.

Thus, the correlation matrix used in the computer program is the predictor matrix, with each predictor's validity in the diagonal cell for that predictor. Each and every element in the matrix is based on the entire sample of N subjects. The first-principle component of this matrix yields the FRA weights. This component has the greatest variance that is possible, representing the best-fitting line through the predictor space after the predictor scales have been transformed by their validities. Two predictors that are highly correlated can, and often do, have the same weight. This enhances the reliability of the composites.

It may be of interest to compare FRA and MR in matrix-algebra form. Weight computation involves the solving of the Lagrange multiplier, λ, through a set of simultaneous linear equations of the form:

$$|r'R^{-1}r - \lambda I| = 0$$

in the case of MR, and

$$|R^{-1}C - \lambda I| = 0$$

in the case of FRA, where

r is the vector of validities,

R is the intercorrelation matrix of predictors with ones in the main diagonal,

I is the identity matrix, and

C is the intercorrelation matrix of predictors with validities in the main diagonal.

The equation for FRA yields predictor weights that maximize the expected value of the intrapair correlation discussed above.

It can be seen that the equations for MR and FRA differ only in the first term. In the case of MR, R-inverse is pre- and postmultiplied by the vector of validities. And in the case of FRA, it is postmultiplied by C, which is the same as R except for the diagonal elements--unities in R, and validities in C. It is of interest to note that the FRA equation is equivalent to the one used by Thomson (1940) to maximize the reliability of a composite, except that the diagonal elements of matrix C were the reliabilities of the respective predictors (see Gulliksen, 1950, p. 346).

For completeness, we should note that the comparable equation for factor analysis is $|C - \lambda I| = 0$ where C is the intercorrelation matrix with communalities in the diagonal. When reliabilities are used, as they often are as communality estimates, the C matrix is the same as the matrix used by Thomson (1940). The remaining difference between factor analysis and maximizing the reliability of a composite is that C is multiplied by R-inverse in the latter case.

The new method is a very important improvement upon multiple regression for small samples. In addition, FRA does not fail at the higher samples sizes as previously proposed methods have done. Thus, it can be used with confidence for all samples sizes as they occur in applied settings.

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APPENDIX

PROOF THAT THE VALIDITY SQUARED IS THE EXPECTED VALUE OF THE CORRELATION BETWEEN TWO SUBSETS MATCHED ON THE CRITERION

PROOF THAT THE VALIDITY SQUARED IS THE EXPECTED VALUE OF THE CORRELATION BETWEEN TWO SUBSETS MATCHED ON THE CRITERION

The sample members are ranked on the basis of their criterion (Y) scores. Then, the sample member with the highest Y score is paired with the second highest, the third highest is paired with the fourth highest, etc. In this way, the sample is divided into two sets, A and B, which correlate as high as possible on the criterion, Y. Set A contains all the odd rank numbers and set B contains all the even rank numbers.

If we assume standard scores, the variance of the differences on a predictor, X, is

$$\sigma_{(A-B)}^2 = \sigma_A^2 + \sigma_B^2 - 2r_{AB}\sigma_A\sigma_B, \qquad (1)$$

where r_{AB} is the correlation between sets A and B on X.

But since $E\sigma_A^2 = E\sigma_B^2 = 1.0$,

$$E\sigma_{(A-B)}^2 = 2(1-r_{AB}). \qquad (2)$$

Now, if we return to the original bivariate distribution X and Y for this sample, the standard error of estimate is

$$\sigma_{YX} = \sigma_Y\sqrt{1-r_{YX}^2}, \qquad (3)$$

and for a given Y score

$$\sigma_{X\cdot Y}^2 = 1-r_{YX}^2. \qquad (4)$$

For the same Y score, the variance of the difference between the pair groups, sets A and B, is

$$\sigma_{(A-B)}^2 = \sigma_A^2 + \sigma_B^2 + 0, \qquad (5)$$

where the zero arises from the fact that $Er_{AB} = 0$ for a given Y score.

But since, for a given Y score,

$$E\sigma_A = E\sigma_B = E\sigma_X, \qquad (6)$$

Equation 5 can be written

$$E\sigma_{(A-B)}^2 = 2\sigma_{X\cdot Y}^2 \qquad (7)$$

or, following Equation 4,

$$E\sigma_{(A-B)}^2 = 2(1-r_{YX}^2). \qquad (8)$$

Notice that Equations 2 and 8 are both based on a conceptually fixed Y. In Equation 2, Y was fixed for each difference by matching. In Equation 8, Y was fixed statistically. Therefore, Equations 2 and 8 are equivalent, and

$$E\left[2(1-r_{AB})\right] = 2(1-r_{YX}^2),$$

$$Er_{AB} = r_{YX}^2.$$

Thus, the validity squared is the expected value of the correlation between two subsets matched on the criterion.

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